Dataset URL : -------------- Dataset has been downloaded from Kagglr. https://www.kaggle.com/datasets/mokar2001/house-price-tehran-iran Dataset description: -------------------- This dataset provides information about Area in square meters Number of bedrooms Has Parking or not Has elevator or not Has warehouse or not The region where the house is placed Price in Toman and USD. Additional Details: ---------------------- Dataset contains 8 columns of tehran house features.

HOUSE PRICE PREDICTION ANALYSIS - TEHRAN HOUSE DATASET

In [1]:
```
#import needed libraries

#for data manipulations
import pandas as pd
import numpy as np

#for ploting data
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="darkgrid",font_scale=1.5)
#for statistical test
import scipy
import statsmodels.formula.api as smf
import statsmodels.api as sm
#for machine learning
from sklearn import model_selection, preprocessing, feature_selection, ensemble, li
from sklearn.model_selection import GridSearchCV, KFold, train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import  ElasticNet, Lasso, LinearRegression, Ridge
from xgboost import XGBRegressor
from sklearn.neighbors import KNeighborsRegressor

import plotly
import plotly.express as px
import plotly.graph_objs as go
import plotly.offline as py
from plotly.offline import iplot
from plotly.subplots import make_subplots
import plotly.figure_factory as ff

import warnings
warnings.filterwarnings("ignore")
```

1. Data Capture and Initial Analysis

In [2]:
```
#reading the data
#understanding data structure
housePrice=pd.read_csv("housePrice.csv")
housePrice.tail()
```

Out[2]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	Price(USD)
3474	86	2	True	True	True	Southern Janatabad	3.500000e+09	116666.67
3475	83	2	True	True	True	Niavaran	6.800000e+09	226666.67
3476	75	2	False	False	False	Parand	3.650000e+08	12166.67
3477	105	2	True	True	True	Dorous	5.600000e+09	186666.67
3478	82	2	False	True	True	Parand	3.600000e+08	12000.00

Exploratory Data Analysis

In [3]:

```
#checking the data infor
housePrice.info()
```

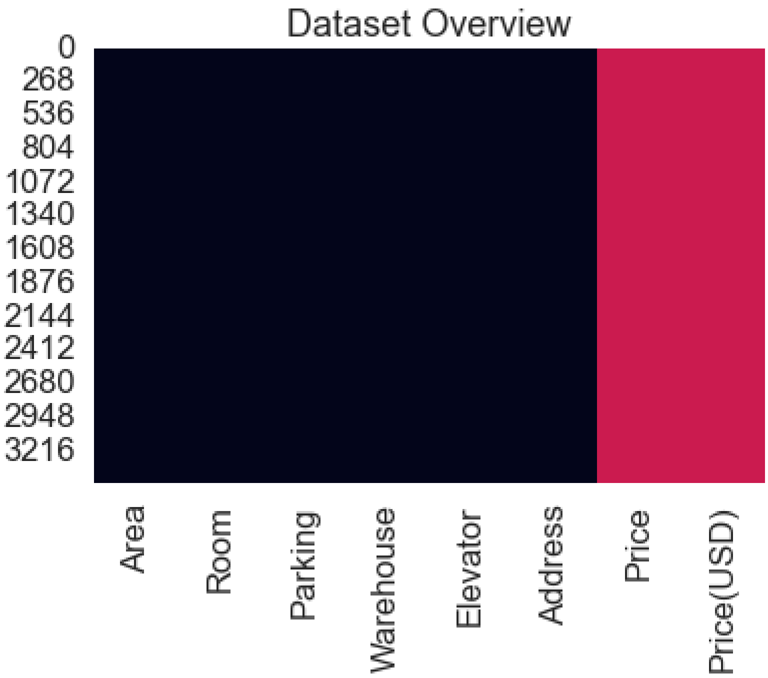
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3479 entries, 0 to 3478
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Area        3479 non-null   object 
 1   Room        3479 non-null   int64  
 2   Parking     3479 non-null   bool   
 3   Warehouse   3479 non-null   bool   
 4   Elevator    3479 non-null   bool   
 5   Address     3456 non-null   object 
 6   Price       3479 non-null   float64
 7   Price(USD)  3479 non-null   float64
dtypes: bool(3), float64(2), int64(1), object(2)
memory usage: 146.2+ KB
```

Insights from the First Glance

In [4]:

```
## Confirming the variables type that we are dealing with
#1. i want to recognised if a column is numeric or categorical data using a self de
def utils_recog_type(data,col,max_cat=20):
    if(data[col].dtype ==  "O") | (data[col].nunique() < max_cat):
        return "cat"
    else:
        return "num"


#i want to plot heatmap to visualized columns type and missing data
dict_cols={col:utils_recog_type(housePrice, col, max_cat=20) for col in housePrice
print(dict_cols)

heatmap=housePrice.isnull()
#print(heatmap)

for k,v in dict_cols.items():
    if v=="num":
        heatmap[k]=heatmap[k].apply(lambda x:0.5 if x is False else 1)
    else:
        heatmap[k]=heatmap[k].apply(lambda x:0 if x is False else 1)
sns.heatmap(heatmap,cbar=False).set_title('Dataset Overview')
plt.show()
```

```
{'Area': 'cat', 'Room': 'cat', 'Parking': 'cat', 'Warehouse': 'cat', 'Elevator':
'cat', 'Address': 'cat', 'Price': 'num', 'Price(USD)': 'num'}
```



> In our dataset, we have both numerical and categorical variables. > The data consist of two targets varibale 'Price' where one is USD conversion of the other in Tehran Currency, which i will later drop one of them > 'Price' is detected as an float and not as an object. > Both 'Area' and 'Address' are categrical varibles, which i will later encode to numerical > The data consist of 3 bool variables 'parking' coded as 1 for parking space available and 0 for no packing space 'Warehouse' coded as 1 for warehouse available and 0 for no warehouse 'Elevator' coded as 1 for elevator available and 0 for no elevator i will later convert this to numerical variable > 'Address' consist of missing that

PROBLEM TO SOLVE

Based on the data Description, We have prediction / regression problem. I wil make prediction on the target variable PRICE I will build a model to get best prediction on the price variable. I will alos get the Model that best predict the outcome For that we will use RMSE(Root Mean Squared Error) and R2

In [5]:
```
dubSum=housePrice.duplicated().sum()
print (f' We have {dubSum} dublicated information')
```

```
 We have 208 dublicated information
```

Missing Values

In [6]:
```
#percentage of missing that
def mValue (data):
    m_number = data.isnull().sum().sort_values(ascending=False)
    m_percent = (data.isnull().sum()/data.isnull().count()).sort_values(ascending=
    m_values = pd.concat([m_number, m_percent], axis=1, keys=['Missing Total', 'Mi
    return m_values

mValue(housePrice)
```

Out[6]:

	Missing Total	Missing %
Address	23	0.006611
Area	0	0.000000
Room	0	0.000000
Parking	0	0.000000
Warehouse	0	0.000000
Elevator	0	0.000000
Price	0	0.000000
Price(USD)	0	0.000000

Based on the above table only Address varibale consist of Missing values which a total 23 and 0.7% of the total observed information. We will deal with this later.

Numerical Features in that data set

In [7]:

```
cat = ['Address', 'Area', 'Parking', 'Warehouse','Elevator']

num = ['Room','Price', 'Price(USD)']
housePrice[num].describe()
```

Out[7]:

	Room	Price	Price(USD)
count	3479.000000	3.479000e+03	3.479000e+03
mean	2.079908	5.359023e+09	1.786341e+05
std	0.758275	8.099935e+09	2.699978e+05
min	0.000000	3.600000e+06	1.200000e+02
25%	2.000000	1.418250e+09	4.727500e+04
50%	2.000000	2.900000e+09	9.666667e+04
75%	2.000000	6.000000e+09	2.000000e+05
max	5.000000	9.240000e+10	3.080000e+06

We have three numerical features in our dataset. All of our numerical features are measured in different scales. Based on the mean & median score differences, we can expect Slightly Right skew on the 'Room' (mean: 2.08 & median: 2.00) left skew on the 'Price' (mean: 5.36 & median: 2.90) And Left skew distribution on the 'Price(USD)' (mean: 1.79 & median: 9.67)

In [8]:

```
#We can now check the skewness
housePrice[num].skew()
```

Out[8]:

```
Room          0.626076
Price         4.779074
Price(USD)    4.779074
dtype: float64
```

Based on the above result the 3 features are positively skewed,Price and Price(USD) right tail

Univarate analysis

In [9]:

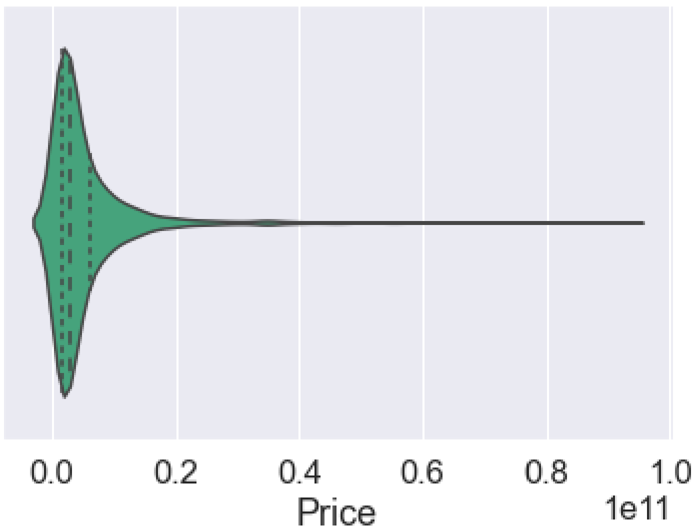
```
plt.figure(figsize=(15,8))
sns.histplot(x=housePrice["Price"] , kde=True,bins=100)
```

```
plt.title('Price Distribution' , color='gray')
```

Out[9]: `Text(0.5, 1.0, 'Price Distribution')`

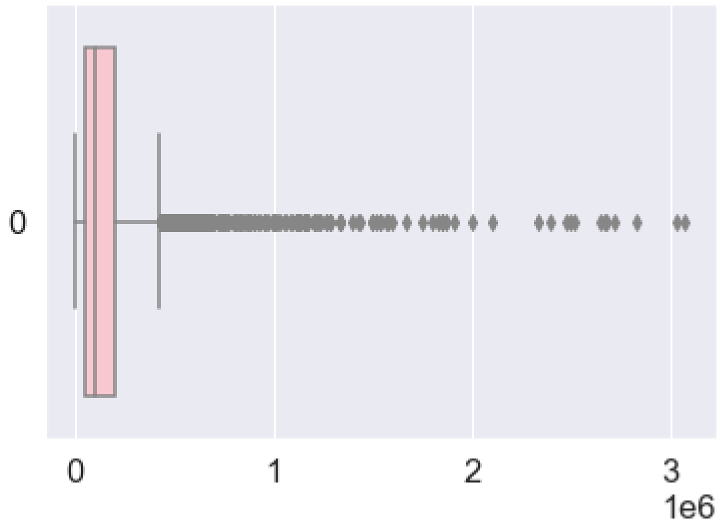
Description As it can be seen , Price feature is Right-Skewed. Most houses have roughly close price in one third of the first part Outliers are obvious now(on the right side)

In [10]:
```
sns.violinplot(x=housePrice['Price'], inner="quartile", color="#36B37E");
```



In [11]:
```
sns.boxplot(data=housePrice['Price(USD)'], orient='h', color='pink')
```

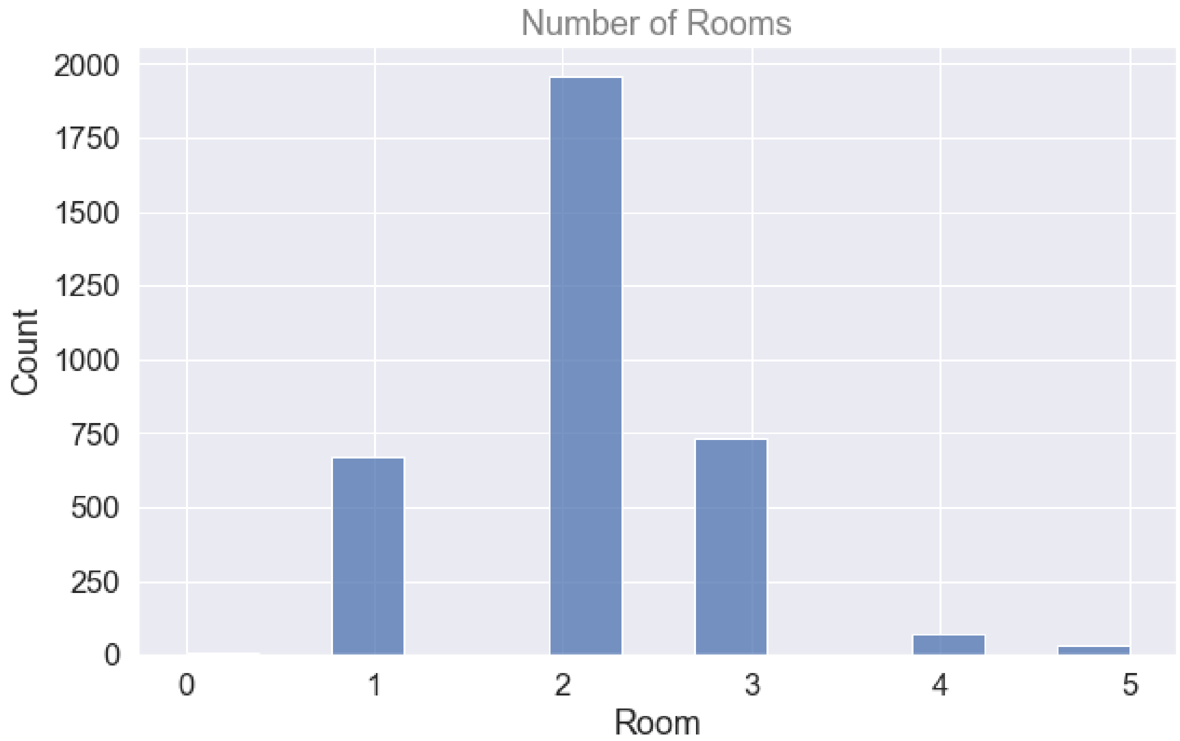
Out[11]: `<AxesSubplot:>`



from the above violin Plot for both Price and Price(USD), we can see that most houses fall between 10000 and 50,000 in USD. we can also see this in the boxplot. The result also reveal presence of outliers in the target variable.

In [12]:
```
plt.figure(figsize=(10,6))
sns.histplot(housePrice["Room"] , palette='Set2' )
plt.title("Number of Rooms" , color='gray')
```

Out[12]:
```
Text(0.5, 1.0, 'Number of Rooms')
```



> The numerical variables as different scales, i will deal with this during data preprocessing > Varibale 'Room' is sligtly skewes while the price has a right tails About 2000 houses have exactly 2 rooms (most houses) Distribution of 1 and 3 rooms are roughly the same (a little more 3 rooms) we have not many houses with 4 or 5 rooms (in total about 150 houses) houses without room is rarely seen Conclusion Mean of rooms is roughly 2.

CATEGORICAL FEATURES

In [13]:
```
# ADDRESS
```

In [14]:
```python
print(housePrice['Address'].value_counts())
housePrice['Address'].unique()
```

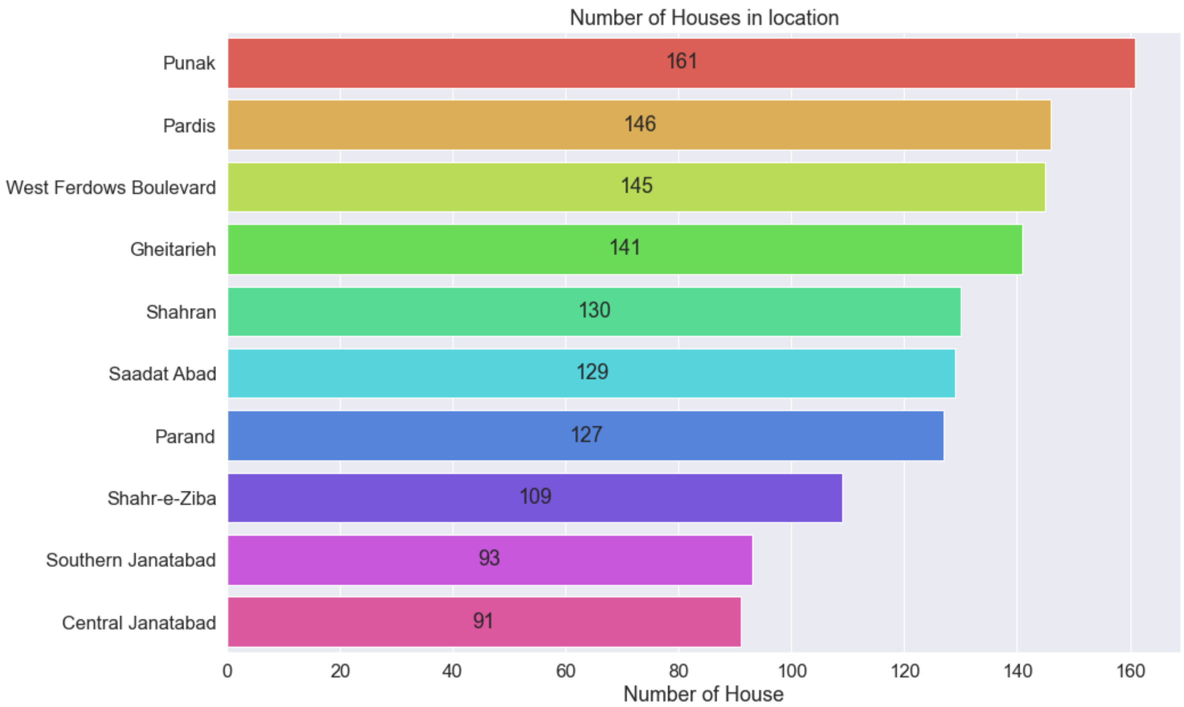
```
Punak                    161
Pardis                   146
West Ferdows Boulevard   145
Gheitarieh               141
Shahran                  130
                        ... 
Chardangeh                 1
Mehrabad                   1
Pakdasht KhatunAbad        1
Kazemabad                  1
Yakhchiabad                1
Name: Address, Length: 192, dtype: int64
```

Out[14]:
```
array(['Shahran', 'Pardis', 'Shahrake Qods', 'Shahrake Gharb',
       'North Program Organization', 'Andisheh', 'West Ferdows Boulevard',
       'Narmak', 'Saadat Abad', 'Zafar', 'Islamshahr', 'Pirouzi',
       'Shahrake Shahid Bagheri', 'Moniriyeh', 'Velenjak', 'Amirieh',
       'Southern Janatabad', 'Salsabil', 'Zargandeh', 'Feiz Garden',
       'Water Organization', nan, 'ShahrAra', 'Gisha', 'Ray', 'Abbasabad',
       'Ostad Moein', 'Farmanieh', 'Parand', 'Punak', 'Qasr-od-Dasht',
       'Aqdasieh', 'Pakdasht', 'Railway', 'Central Janatabad',
       'East Ferdows Boulevard', 'Pakdasht KhatunAbad', 'Sattarkhan',
       'Baghestan', 'Shahryar', 'Northern Janatabad', 'Daryan No',
       'Southern Program Organization', 'Rudhen', 'West Pars', 'Afsarieh',
       'Marzdaran', 'Dorous', 'Sadeghieh', 'Chahardangeh', 'Baqershahr',
       'Jeyhoon', 'Lavizan', 'Shams Abad', 'Fatemi',
       'Keshavarz Boulevard', 'Kahrizak', 'Qarchak',
       'Northren Jamalzadeh', 'Azarbaijan', 'Bahar',
       'Persian Gulf Martyrs Lake', 'Beryanak', 'Heshmatieh',
       'Elm-o-Sanat', 'Golestan', 'Shahr-e-Ziba', 'Pasdaran',
       'Chardivari', 'Gheitarieh', 'Kamranieh', 'Gholhak', 'Heravi',
       'Hashemi', 'Dehkade Olampic', 'Damavand', 'Republic', 'Zaferanieh',
       'Qazvin Imamzadeh Hassan', 'Niavaran', 'Valiasr', 'Qalandari',
       'Amir Bahador', 'Ekhtiarieh', 'Ekbatan', 'Absard', 'Haft Tir',
       'Mahallati', 'Ozgol', 'Tajrish', 'Abazar', 'Koohsar', 'Hekmat',
       'Parastar', 'Lavasan', 'Majidieh', 'Southern Chitgar', 'Karimkhan',
       'Si Metri Ji', 'Karoon', 'Northern Chitgar', 'East Pars', 'Kook',
       'Air force', 'Sohanak', 'Komeil', 'Azadshahr', 'Zibadasht',
       'Amirabad', 'Dezashib', 'Elahieh', 'Mirdamad', 'Razi', 'Jordan',
       'Mahmoudieh', 'Shahedshahr', 'Yaftabad', 'Mehran', 'Nasim Shahr',
       'Tenant', 'Chardangeh', 'Fallah', 'Eskandari', 'Shahrakeh Naft',
       'Ajudaniye', 'Tehransar', 'Nawab', 'Yousef Abad',
       'Northern Suhrawardi', 'Villa', 'Hakimiyeh', 'Nezamabad',
       'Garden of Saba', 'Tarasht', 'Azari', 'Shahrake Apadana', 'Araj',
       'Vahidieh', 'Malard', 'Shahrake Azadi', 'Darband', 'Vanak',
       'Tehran Now', 'Darabad', 'Eram', 'Atabak', 'Sabalan', 'SabaShahr',
       'Shahrake Madaen', 'Waterfall', 'Ahang', 'Salehabad', 'Pishva',
       'Enghelab', 'Islamshahr Elahieh', 'Ray - Montazeri',
       'Firoozkooh Kuhsar', 'Ghoba', 'Mehrabad', 'Southern Suhrawardi',
       'Abuzar', 'Dolatabad', 'Hor Square', 'Taslihat', 'Kazemabad',
       'Robat Karim', 'Ray - Pilgosh', 'Ghiyamdasht', 'Telecommunication',
       'Mirza Shirazi', 'Gandhi', 'Argentina', 'Seyed Khandan',
       'Shahrake Quds', 'Safadasht', 'Khademabad Garden', 'Hassan Abad',
       'Chidz', 'Khavaran', 'Boloorsazi', 'Mehrabad River River',
       'Varamin - Beheshti', 'Shoosh', 'Thirteen November', 'Darakeh',
       'Aliabad South', 'Alborz Complex', 'Firoozkooh', 'Vahidiyeh',
       'Shadabad', 'Naziabad', 'Javadiyeh', 'Yakhchiabad'], dtype=object)
```

In [15]:
```python
addr = housePrice['Address'].value_counts().copy()
addr = addr[:10]
fig, ax = plt.subplots(figsize=(15,10))
```

```
sns.barplot(x=addr.values, y=addr.index,ax=ax,  palette = 'hls',

            capsize = 0.05,
            saturation = 8,
            errcolor = 'gray', errwidth = 2,
            ci = 'sd' )
ax.bar_label(ax.containers[0], label_type='center')
plt.xlabel('Number of House')
plt.title('Number of Houses in location')
```

Out[15]: Text(0.5, 1.0, 'Number of Houses in location')



The above result shows the percentage and total numbr of houses in a particular location. 'punka' has the highest of number houses(161),followeed by Pardis(146),West Ferdows Boulevard(145), Gheitarieh,Shahran e.t.c Total unique Address is 191. We will later compare house prices in various area, to see if there price a flat depend on a particular enviroment.

House AREA

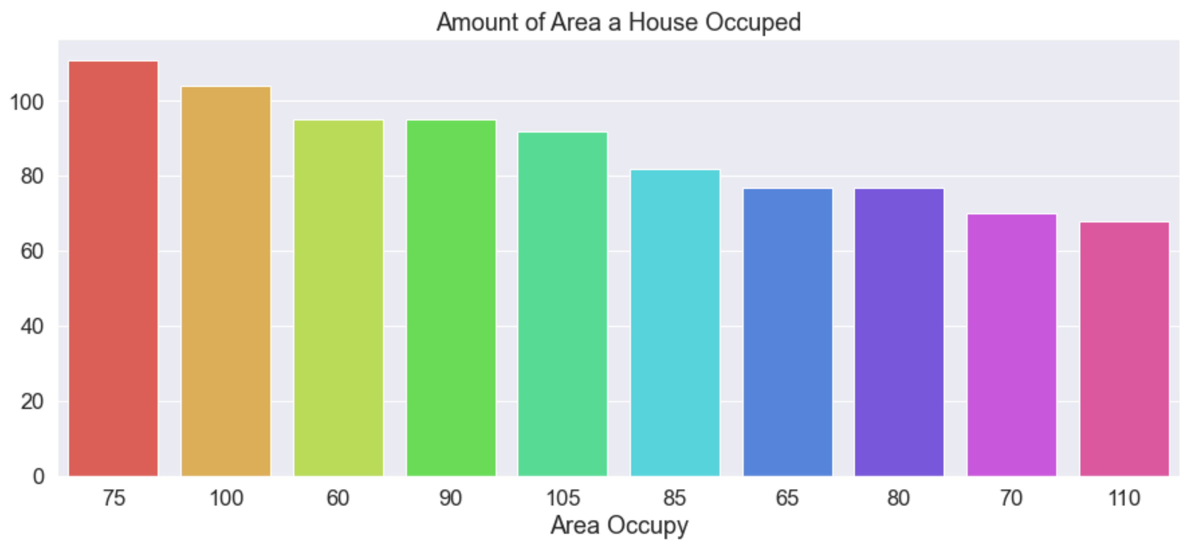
In [16]:
```
housePrice['Area'].sort_values().head(20)
```

Out[16]:
```
807              1,000
709     16,160,000,000
2802     2,550,000,000
570      3,310,000,000
2171             3,600
1604     8,400,000,000
934                100
1080               100
1595               100
1597               100
3137               100
1608               100
180                100
2831               100
1590               100
2332               100
2943               100
192                100
2733               100
1655               100
Name: Area, dtype: object
```

By Applying sorting to the column area an there values that are outrageous, i would have user histogram to check for the distribution but unfortunately the feature is categorical varibale. I will later convert this to a numerical data type.

In [17]:
```
aR = housePrice['Area'].value_counts().copy()
aR = aR[:10]
fig, ax = plt.subplots(figsize=(15,6))
sns.barplot(x=aR.index, y=aR.values,ax=ax, palette = 'hls',

            capsize = 0.05,
            saturation = 8,
            errcolor = 'gray', errwidth = 2,
            ci = 'sd' )
plt.xlabel('Area Occupy')
plt.title('Amount of Area a House Occuped')
```

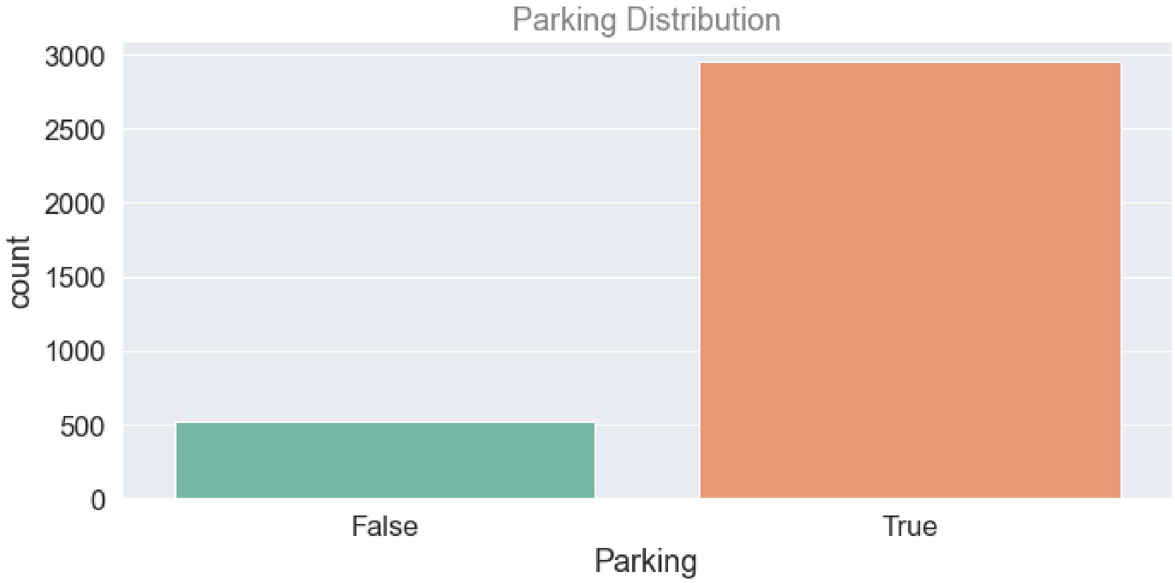
Out[17]:
```
Text(0.5, 1.0, 'Amount of Area a House Occuped')
```

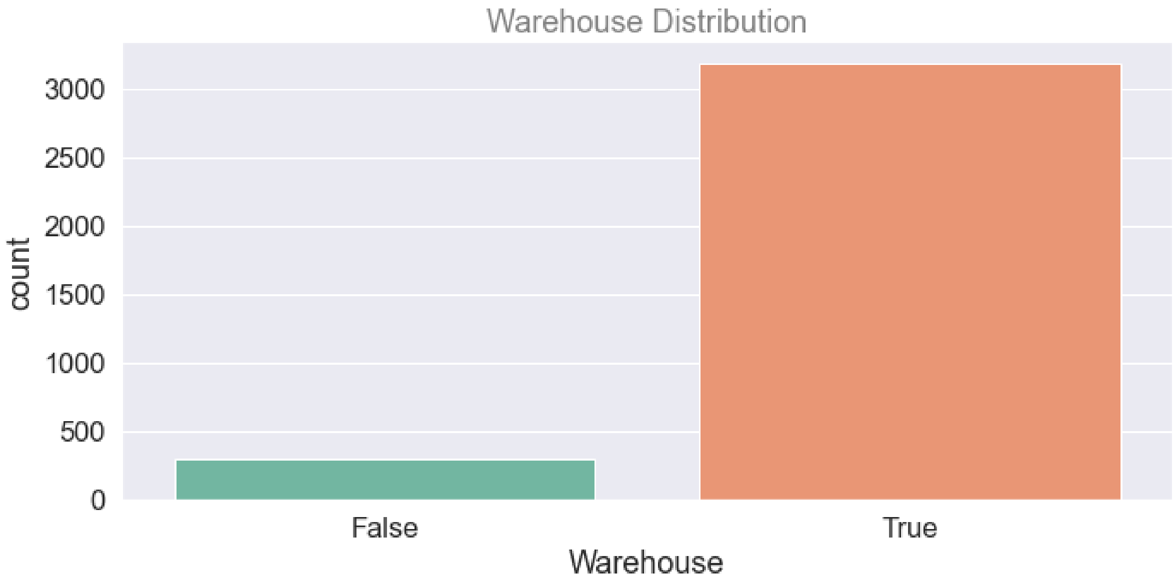


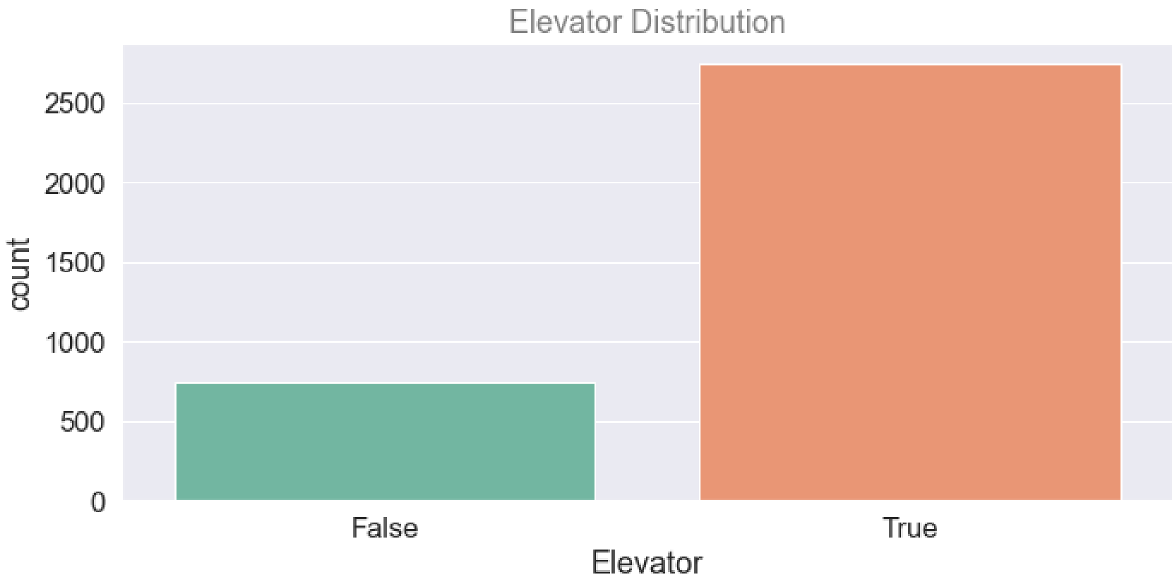
PARKING, WAREHOUSE, ELEVATOR AVAILABILITY

In [18]:
```
print (f'{round(housePrice["Parking"].value_counts(normalize=True)*100,2)}')
print (f'{round(housePrice["Warehouse"].value_counts(normalize=True)*100,2)}')
print (f'{round(housePrice["Elevator"].value_counts(normalize=True)*100,2)}')


boo = ['Parking', 'Warehouse', 'Elevator']
plt.figure(figsize=(10,15))
for inx , col in enumerate(boo):
    plt.subplot(3,1,inx+1)
    sns.countplot(x=col,data=housePrice , palette='Set2')
    plt.title(f'{col} Distribution' , color='gray')
    plt.tight_layout()
```

```
True     84.79
False    15.21
Name: Parking, dtype: float64
True     91.46
False     8.54
Name: Warehouse, dtype: float64
True     78.73
False    21.27
Name: Elevator, dtype: float64
```







The result above shows that 84.79% of the houses has Parking lot, 91.46 of them has a warehouse and 78.73% ofd them has ElevatorGENERAL OBSERVATION FROM EACH FEATURE > Two targets varibale 'Price' where one is USD conversion of the other in Tehran Currency > 'Price' is detected as an float and not as an object. > Both 'Area' and 'Address' are categrical varibles > The data consist of 3 bool variables 'parking' coded as True for parking space available and False for no packing space 'Warehouse' coded as True for warehouse available and False for no warehouse 'Elevator' coded as True for elevator available and False for no elevator > 'Address' consist of 23 missing value > ThE whole data consist of 208 dublicated values 'punka' has the highest of number houses(161),followeed by Pardis,West Ferdows Boulevard, Gheitarieh,Shahran e.t.c > Total unique Address is 191. > Price consist of outliers > The numerical variables as different scales, i will deal with this during data preprocessing > Varibale 'Room' is sligtly skewes while the price has a right tails > Area and price consist of outrageous values which far from than most of the observed information and may be cause for the presence of outliers

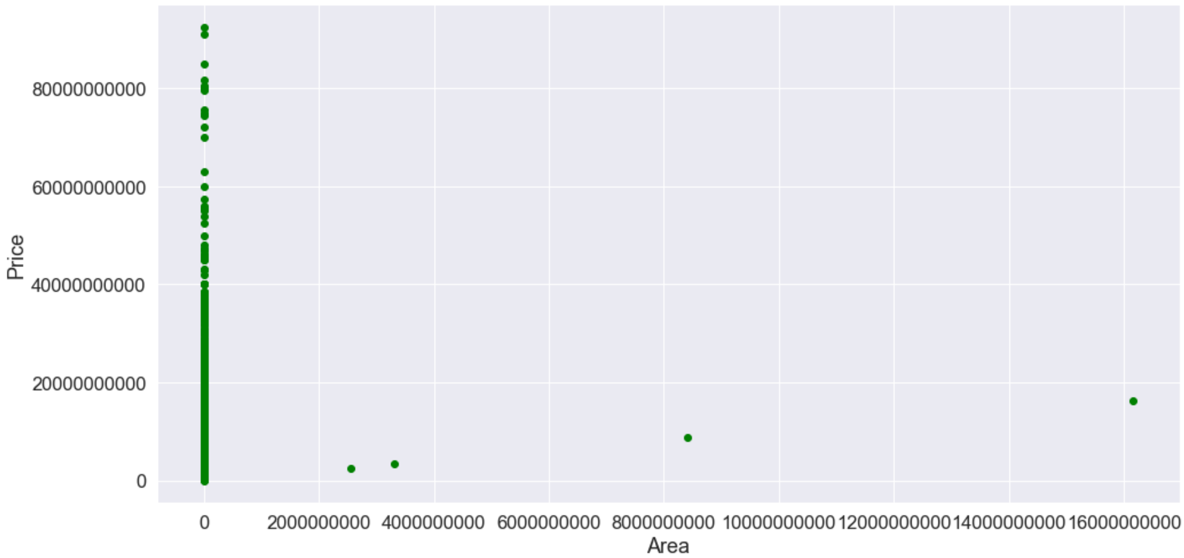
BIVARIATE ANALYSIS

I will be ploting each features() against target varible price

NUMERICAL FEATURE

AREA VS PRICE

In [19]:
```
#converting Area data type and replacing space with ,
housePri=housePrice
housePri["Area"] = housePri["Area"].apply(lambda x: float(x.split()[0].replace(','
housePri["Area"].astype(str).astype(float)

#ploting Price against Area
plt.figure(figsize = (16,8))
plt.scatter(housePri['Area'], housePri['Price'],  color='green')
plt.xlabel("Area")
plt.ylabel("Price")
plt.ticklabel_format(useOffset=False, style='plain')
plt.show()
```



To be able to plot area against price i converted the data type and replace the empty space with a ',' The graph shows outrageous area dimensions and also depicts that most of the prices are tagged to no area, and this is abnormal. The result clearly shows that there are outliers withing the data especially within the area and price. I would like to investigate this by sorting the whole dataset on Area.

In [20]:
```
#Raw Dataset sorted based on Area
housePri.sort_values(by="Area", ascending=False).head(15)
```

Out[20]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	Price(USD)
709	1.616000e+10	3	True	True	True	Pasdaran	1.616000e+10	538666.67
1604	8.400000e+09	2	True	True	True	Gheitarieh	8.700000e+09	290000.00
570	3.310000e+09	2	True	True	True	Ostad Moein	3.310000e+09	110333.33
2802	2.550000e+09	2	True	True	True	Central Janatabad	2.550000e+09	85000.00
2171	3.600000e+03	2	False	False	False	Shahryar	9.720000e+09	324000.00
807	1.000000e+03	2	True	True	False	Damavand	7.000000e+09	233333.33
1694	9.290000e+02	5	True	True	False	Zafar	8.000000e+10	2666666.67
1974	9.000000e+02	3	True	True	False	Damavand	8.500000e+09	283333.33
573	8.630000e+02	2	True	True	True	Gheitarieh	7.830000e+09	261000.00
831	7.500000e+02	5	True	True	True	Mahmoudieh	7.500000e+10	2500000.00
3115	7.500000e+02	5	True	True	False	Varamin - Beheshti	3.500000e+09	116666.67
1810	7.050000e+02	5	True	True	False	Abazar	9.100000e+10	3033333.33
2647	7.000000e+02	3	True	True	False	Damavand	7.000000e+09	233333.33
2481	7.000000e+02	3	True	True	False	Damavand	4.500000e+09	150000.00
819	6.800000e+02	5	True	True	False	Ekhtiarieh	8.160000e+10	2720000.00

In [21]:

```
#getting the list of Houses with this outrageous Area measurement
housePri[housePri['Area']>3500]
```

Out[21]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	Price(USD)
570	3.310000e+09	2	True	True	True	Ostad Moein	3.310000e+09	110333.33
709	1.616000e+10	3	True	True	True	Pasdaran	1.616000e+10	538666.67
1604	8.400000e+09	2	True	True	True	Gheitarieh	8.700000e+09	290000.00
2171	3.600000e+03	2	False	False	False	Shahryar	9.720000e+09	324000.00
2802	2.550000e+09	2	True	True	True	Central Janatabad	2.550000e+09	85000.00

The presence of outliers can now easily be proved because one of the flat recorded for this outlier has only 2 rooms, no parking space, no warehouse, no elevator and the price is said to be extremely high. but considering the Location at which the house is located is at the suburb of Tehran which may likely be expensive.

CATEGORICAL FEATURES

In [22]:

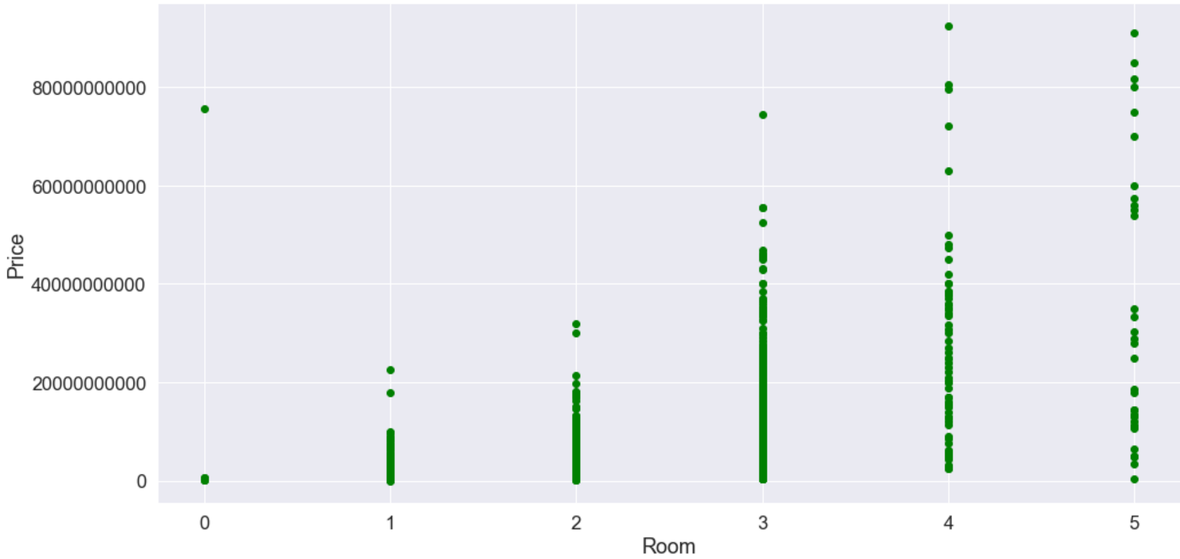
```
def cat_v_tG(hou, feature):
    plt.grid(True)
    ax = sns.boxenplot(data=hou, x=feature, y='Price')
    ax.set_title(f'{feature} vs price', fontdict={'fontsize': 18})

# draw the countplot of a categorical variable
```

```python
def cat_cplot(hou, feature):
    plt.grid(True)
    ax = sns.countplot(x=hou[feature])
    ax.set_title(f'{feature}\'s count', fontdict={'fontsize': 18})


cat_features = ['Room','Parking','Warehouse','Elevator']
```

ROOM VS PRICE

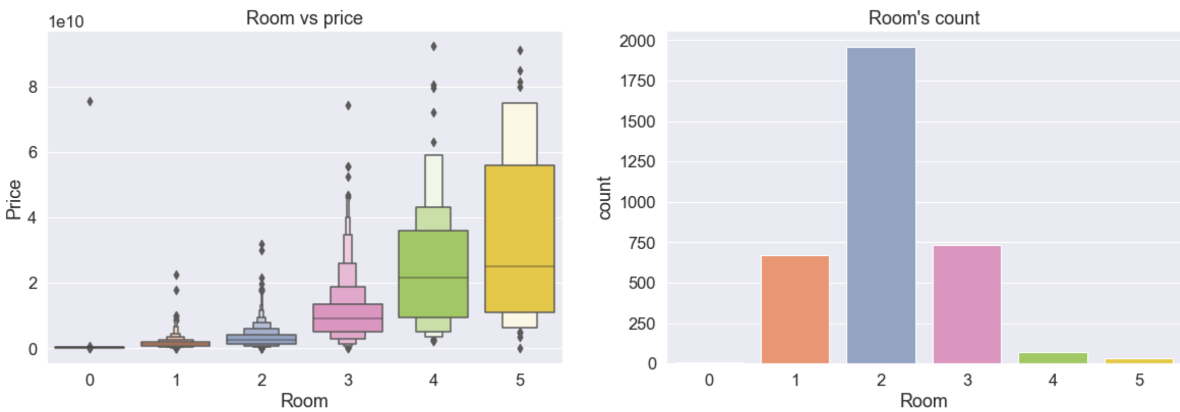
In [23]:

```python
#ROOM VS PRICE
plt.figure(figsize = (16,8))
plt.scatter(housePri['Room'], housePri['Price'],  color='green')
plt.xlabel("Room")
plt.ylabel("Price")
plt.ticklabel_format(useOffset=False, style='plain')
plt.show()
```



In [24]:

```python
plt.figure(figsize=(20, 6))
sns.set_palette('Set2')
plt.subplot(1, 2, 1)
cat_v_tG(housePri, cat_features[0])

plt.subplot(1, 2, 2)
cat_cplot(housePri, cat_features[0])
plt.show()
```

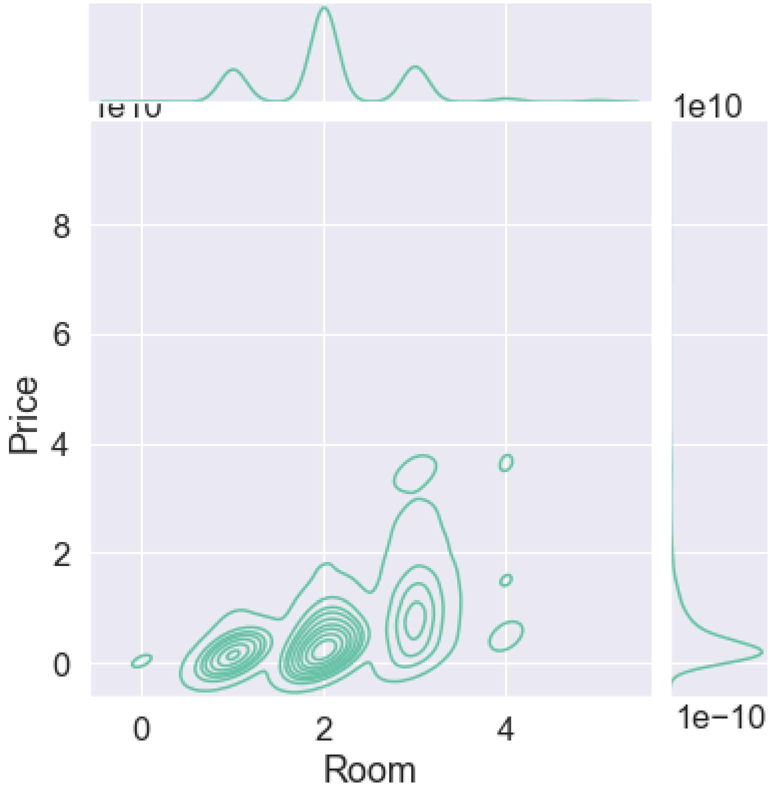


In [25]:

```python
sns.jointplot(x = "Room", y = "Price", kind = "kde", data = housePri)
```

Out[25]:

```
<seaborn.axisgrid.JointGrid at 0x22fc7446c40>
```



Insights: - The majority of houses in this dataset has 2 rooms. - All the houses in this dataset has 0 to 5 rooms. - Usually, flat with higher rooms are naturally expensive. That is, the price goes up when the number of rooms increases. - An exception is when the number of bedrooms is 0, the price is the highest - Most houses with 5 rooms are without elevators. - it seems there is an outliers within. Let me investigate this

In [26]:
```
housePri[(housePri['Room']== 0) & (housePri['Price']> 20000000000)]
```

Out[26]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	Price(USD)
3107	630.0	0	False	False	False	Tajrish	7.560000e+10	2520000.0

In [27]:
```
housePri[(housePri['Address']== "Tajrish")]
```

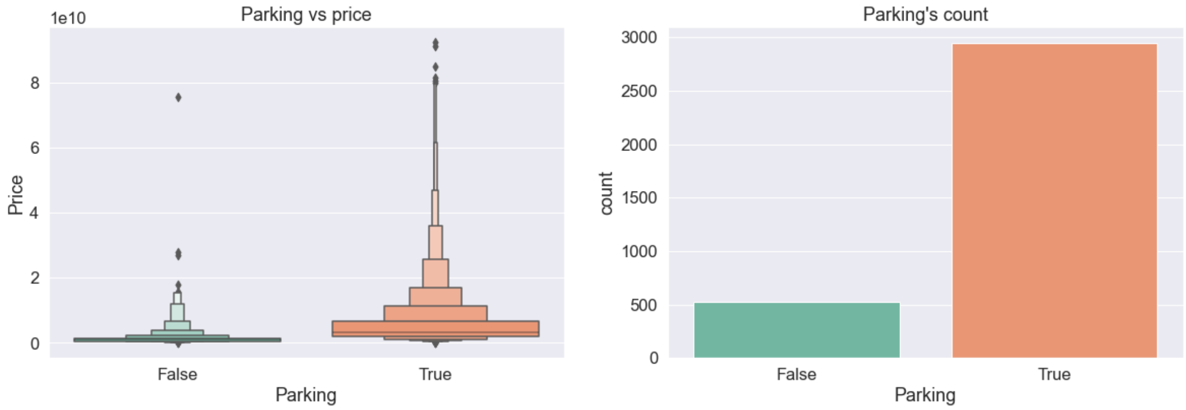
Out[27]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	Price(USD)
355	110.0	2	True	True	True	Tajrish	6.600000e+09	220000.00
1148	115.0	2	True	True	True	Tajrish	8.200000e+09	273333.33
2584	300.0	4	True	True	True	Tajrish	9.000000e+09	300000.00
2769	100.0	2	True	True	True	Tajrish	5.700000e+09	190000.00
2831	100.0	2	True	True	True	Tajrish	5.700000e+09	190000.00
3096	150.0	3	True	True	True	Tajrish	1.275000e+10	425000.00
3107	630.0	0	False	False	False	Tajrish	7.560000e+10	2520000.00

Parking VS Price

In [28]:
```
plt.figure(figsize=(20, 6))
sns.set_palette('Set2')
plt.subplot(1, 2, 1)
cat_v_tG(housePri, cat_features[1])

plt.subplot(1, 2, 2)
```

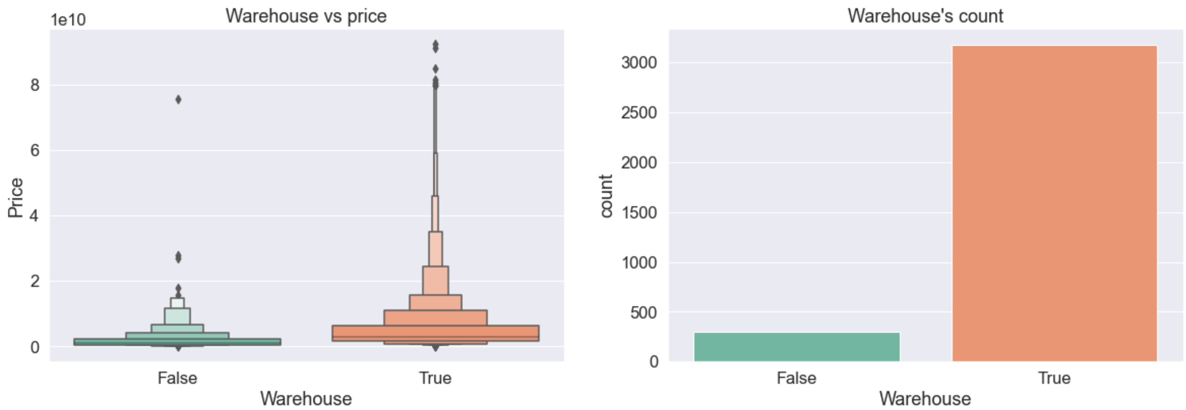
```
cat_cplot(housePri, cat_features[1])
plt.show()
```



Insight - Most of the flat in this dataset has Parking space - The price of the flat with parking is more expensive than those with no parking

Warehouse vs Price

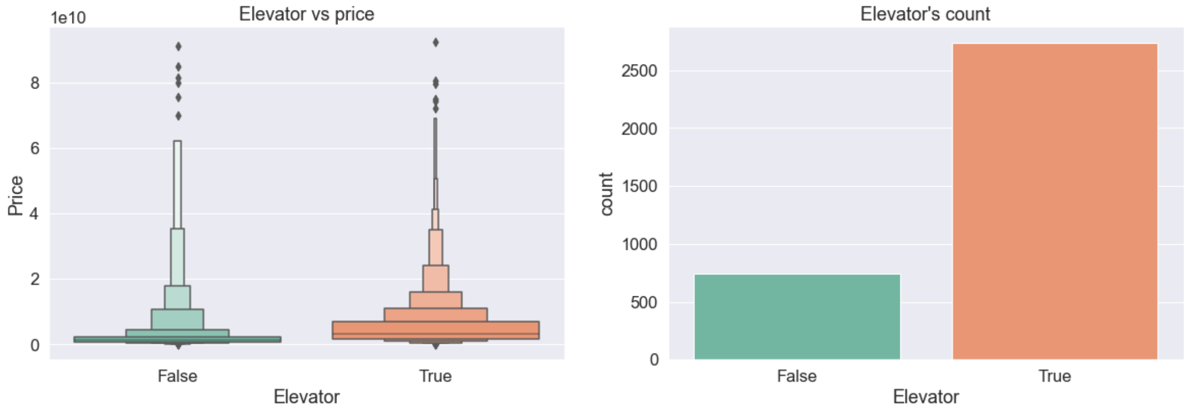
In [29]:
```
plt.figure(figsize=(20, 6))
sns.set_palette('Set2')
plt.subplot(1, 2, 1)
cat_v_tG(housePri, cat_features[2])

plt.subplot(1, 2, 2)
cat_cplot(housePri, cat_features[2])
plt.show()
```



Insight - Most of the flat in this dataset has a Warehouse space - The price of the flat with Warehouse is more expensive than those with no Warehouse

Elevator vs Price

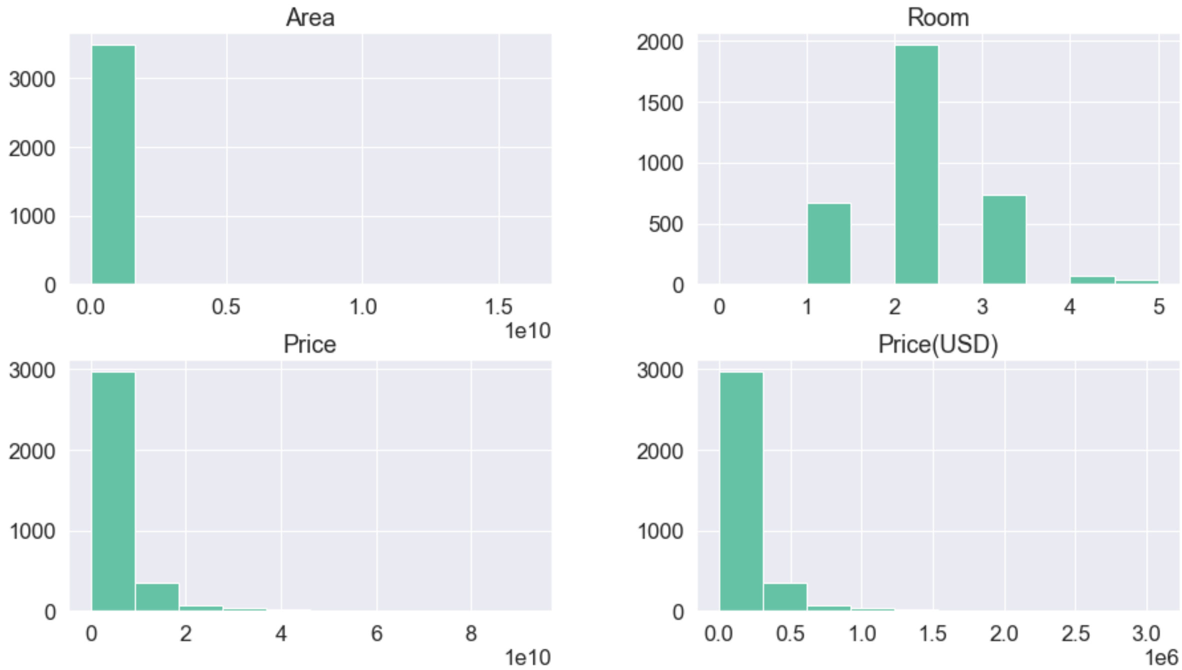
In [30]:
```
plt.figure(figsize=(20, 6))
sns.set_palette('Set2')
plt.subplot(1, 2, 1)
cat_v_tG(housePri, cat_features[3])

plt.subplot(1, 2, 2)
cat_cplot(housePri, cat_features[3])
plt.show()
```



Insight - Most of the flat in this dataset has a Elevator space - The price of the flat with Warehouse is more Elevator than those with no Elevator

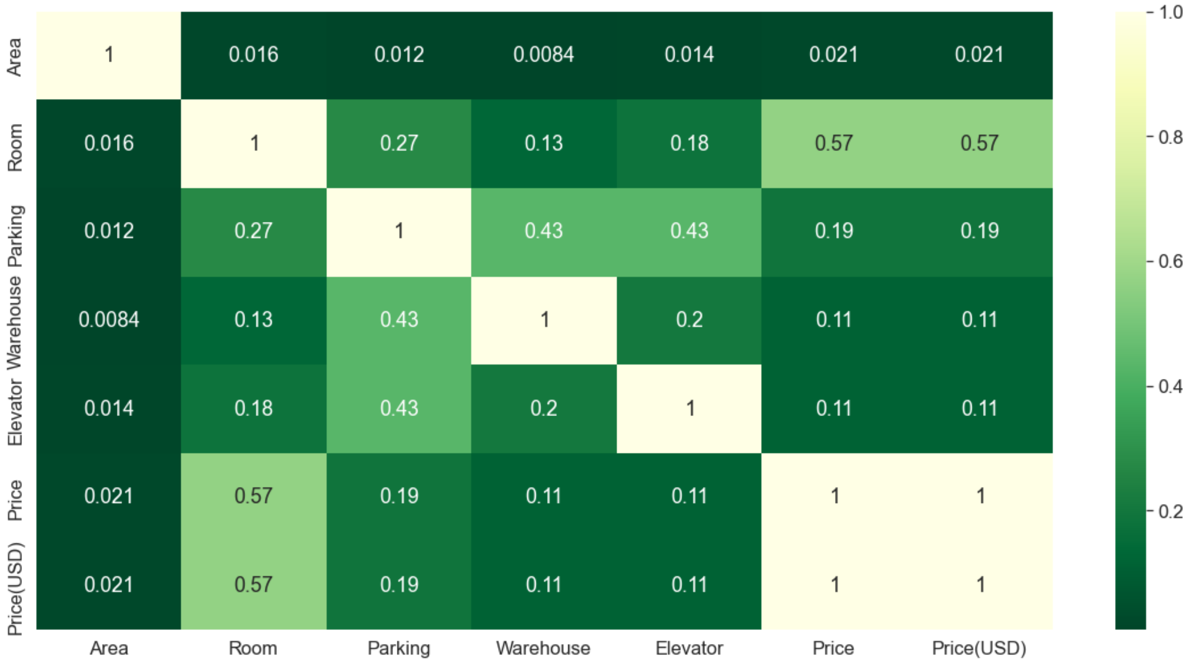
In [31]:
```
housePri.hist(figsize=(15,8))
```

Out[31]:
```
array([[<AxesSubplot:title={'center':'Area'}>,
        <AxesSubplot:title={'center':'Room'}>],
       [<AxesSubplot:title={'center':'Price'}>,
        <AxesSubplot:title={'center':'Price(USD)'}>]], dtype=object)
```



In [32]:
```
plt.figure(figsize=(20,10))
sns.heatmap(housePri.corr(), annot=True, cmap="YlGn_r")
```

Out[32]:
```
<AxesSubplot:>
```



As observed in Univariate analysis for Column Area and price which consist outrageous values, this was also observed from the distribution of Price and Boxplot which shows that price has a positive skew to the right trail. i will remove this column later in data processing. > To avoid multicollinearity within that data I will also drop column Price(USD)

DATA PRE-PROCESSING

In [33]:
```
#copying the orginal dataset
housePri_copy=housePri.copy()
```

WHAT TO DO > REMOVING OUTLIERS FROM PRICE AND AREA > DROPING MISSING ROWS > CONVERT PARKING, WAREHOUSE, ELEVATOR FROM BOOLEAN TO NUMERIC > REMOVING VARIABLES THAT LEAD TO MULTICOLLINEARITY(PRICE(USD))

In [34]:
```
#Converting Boolean type to integers
housePri["Parking"] =housePri['Parking'].astype('int')
housePri["Warehouse"] = housePri['Warehouse'].astype('int')
housePri["Elevator"] = housePri['Elevator'].astype('int')
```

In [35]:
```
housePri.drop(['Price(USD)'], axis=1, inplace=True)
housePri = housePri.drop([709, 1604, 570, 2802])
housePri
```

Out[35]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price
0	63.0	1	1	1	1	Shahran	1.850000e+09
1	60.0	1	1	1	1	Shahran	1.850000e+09
2	79.0	2	1	1	1	Pardis	5.500000e+08
3	95.0	2	1	1	1	Shahrake Qods	9.025000e+08
4	123.0	2	1	1	1	Shahrake Gharb	7.000000e+09
...	...	...	...	...	...	...	...
3474	86.0	2	1	1	1	Southern Janatabad	3.500000e+09
3475	83.0	2	1	1	1	Niavaran	6.800000e+09
3476	75.0	2	0	0	0	Parand	3.650000e+08
3477	105.0	2	1	1	1	Dorous	5.600000e+09
3478	82.0	2	0	1	1	Parand	3.600000e+08

3475 rows × 7 columns

i have drop the Price in USD to avoid multicollinearity and also drop rows with ID 709, 1604, 570, 2802 as they reflect outrageous price and area which resulted into outliers within the data. To be sure the data is now without outliers i will verify that by ploting Area and Price graph.

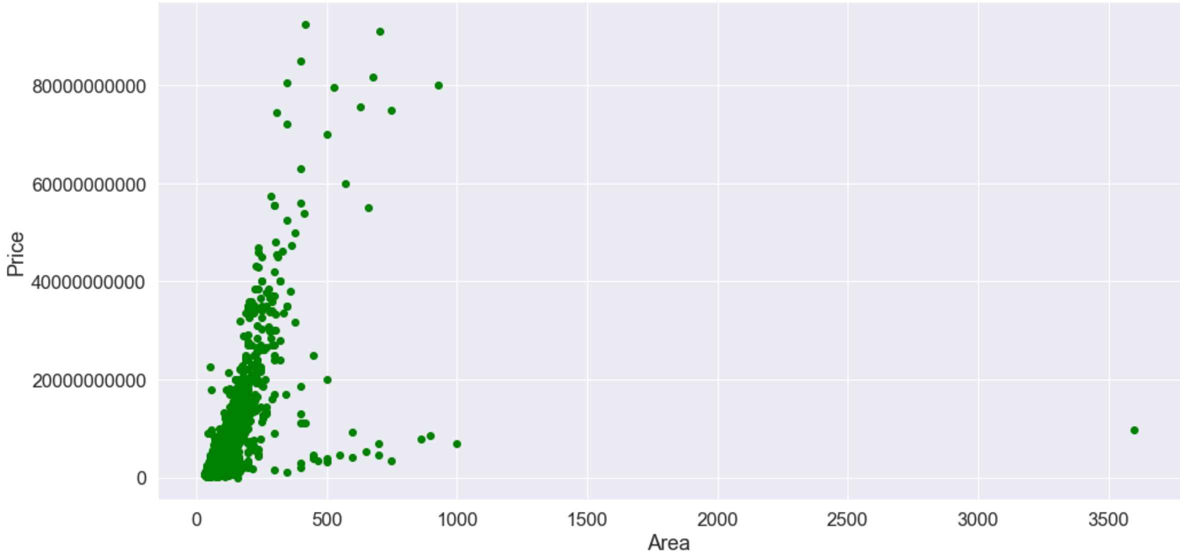
In [36]:

```
housePri=housePri.dropna()
housePri.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3452 entries, 0 to 3478
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Area       3452 non-null   float64
 1   Room       3452 non-null   int64  
 2   Parking    3452 non-null   int32  
 3   Warehouse  3452 non-null   int32  
 4   Elevator   3452 non-null   int32  
 5   Address    3452 non-null   object 
 6   Price      3452 non-null   float64
dtypes: float64(2), int32(3), int64(1), object(1)
memory usage: 175.3+ KB
```

In [37]:

```
#AREA VS PRICE
plt.figure(figsize = (16,8))
plt.scatter(housePri['Area'], housePri['Price'],  color='green')
plt.xlabel("Area")
plt.ylabel("Price")
plt.ticklabel_format(useOffset=False, style='plain')
plt.show()
```



The graph depict that as area goes up the price of the house increases, and this is normal. The result clearly shows that there are still outliers withing the data as we have one issolated point to the right of the graph. The point is shown at point higher that the scale of the area. I would like to investigate this by getting the list of area above 3500

In [38]:
```
#getting the list of Houses above 3500 in dimension
housePri[housePri['Area']>3500]
```

Out[38]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price
2171	3600.0	2	0	0	0	Shahryar	9.720000e+09

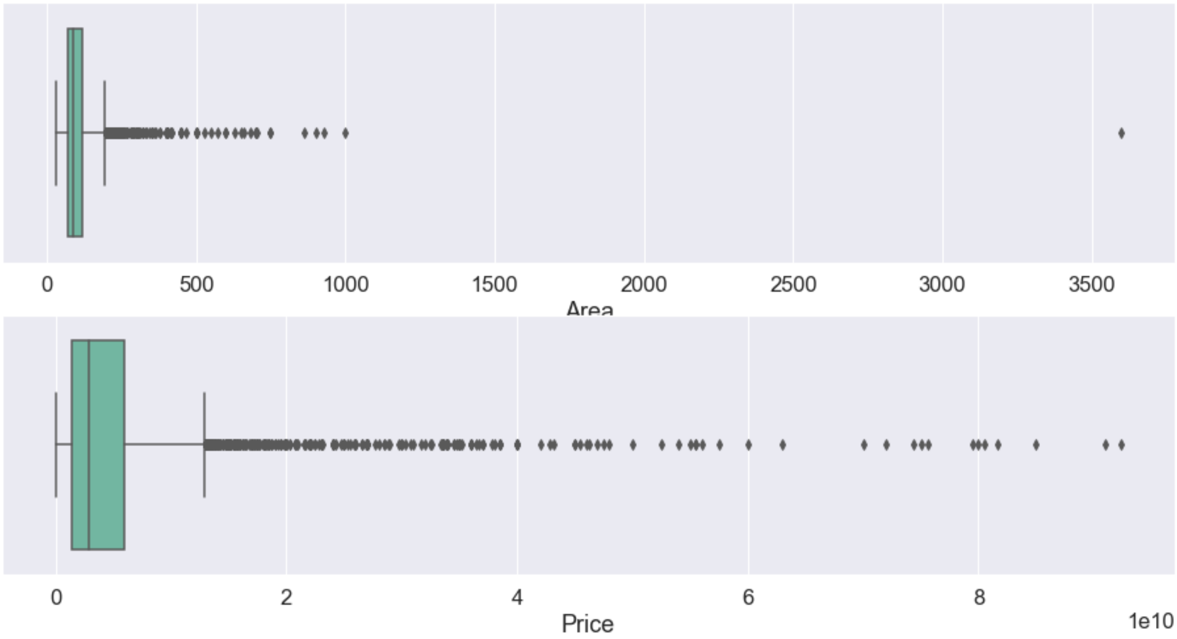
Now i found one information that is responsible for outliers, the observed information has only 2 rooms, no parking space, no warehouse, no elevator and the price is said to be extremely high, but considering the Location at which the house is located is at the suburb of Tehran which may likely be expensive. let me use another function to alos confirm this result

In [39]:
```
housePri.skew()
```

Out[39]:
```
Area         17.605814
Room          0.624244
Parking      -1.932278
Warehouse    -2.973597
Elevator     -1.403149
Price         4.767098
dtype: float64
```

In [40]:
```
plt.figure(figsize = (16,8))

plt.subplot(2,1,1)
sns.boxplot(x =housePri['Area'])

plt.subplot(2,1,2)
sns.boxplot(x = housePri['Price'])
```

Out[40]:
```
<AxesSubplot:xlabel='Price'>
```



Using skewness and box plot function reveal more information on the hinden outliers. The result shows that there are still outliers in price as well,Even after removing some outreagous values from the data. To remove this outliers by writing simple function.

In [41]:
```
#REMOVING OUTLIERS
#i want to get the value of the outliers using interquaritle ranges
#i wil define interquartiles range functions that will give me the IQR values and 
def Up_lw_qrt(data):
    Qrt1=np.percentile(data,25)
    Qrt3=np.percentile(data,75)
    IQR=Qrt3 - Qrt1
    #i want to get the lower and uper quartile now
    lQrt=Qrt1 - (1.5 * IQR)
    UQrt=Qrt3 + (1.5 * IQR)
    return lQrt,UQrt

#i want to show the lower and upper uartiel for this two column Price and Area
l_area,u_area=Up_lw_qrt(housePri.Area)
l_price,u_price=Up_lw_qrt(housePri.Price)

print(f"Lower Price limit is:{l_price:,}")
print(f"Uper Price limit is:{u_price:,}")
print(f"Lower Area limit is:{l_area:0.2f}")
print(f"Uper Area limit is:{u_area:0.2f}")

#area outiers

a_outliers=np.where(housePri.Area > u_area)
p_outliers=np.where(housePri.Price > u_price)
total_outliers= np.union1d(a_outliers,p_outliers)
print(f"Number of Area Outliers:{len(housePri.Area.iloc[a_outliers])}")
print(f"Number of Price Outliers:{len(housePri.Price.iloc[p_outliers])}")
print(f"Number of Total Outliers:{len(housePri.Area.iloc[total_outliers])}")

housePri.Area.iloc[a_outliers]=np.nan
housePri.Price.iloc[p_outliers]=np.nan
```

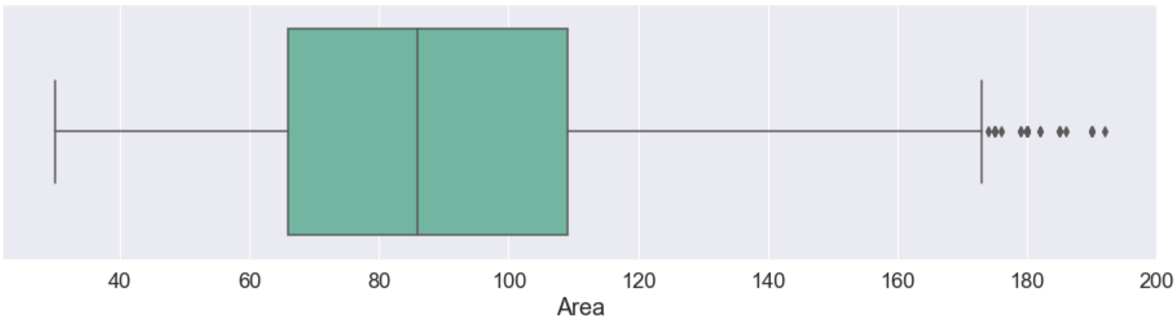
```
Lower Price limit is:-5,450,625,000.0
Uper Price limit is:12,870,375,000.0
Lower Area limit is:-7.50
Uper Area limit is:196.50
Number of Area Outliers:240
Number of Price Outliers:309
Number of Total Outliers:363
```

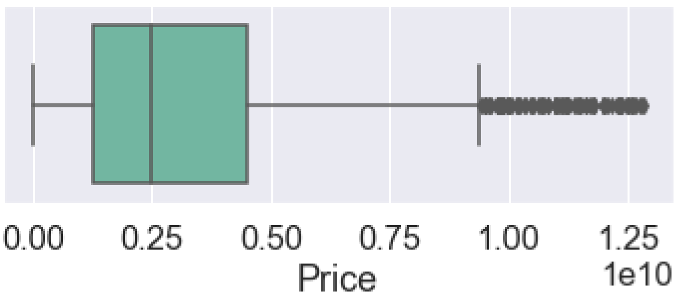
I defined a functions to identify features with outliers and alos to replace the outliers with 'nan'. The result above shows that there 240 outliers in Area, 309 in Price and the total outliers is estimated to be 363. I will drop this outliers.

In [42]:
```
housePri=housePri.dropna(axis=0)
housePri.isnull().sum()
```

Out[42]:
```
Area         0
Room         0
Parking      0
Warehouse    0
Elevator     0
Address      0
Price        0
dtype: int64
```

In [43]:
```
#i want to plot the new area and price varibale to check and confirm that the outl
plt.figure(figsize = (16,8))
plt.subplot(2,1,1)
sns.boxplot(x=housePri.Area)
plt.show()

plt.subplot(2,1,2)
sns.boxplot(x=housePri.Price)
plt.show()

print("Here is the skewness after droping outliers",housePri.skew())
#let me also check cross correlation of the data using pairplot of the whole datase
```

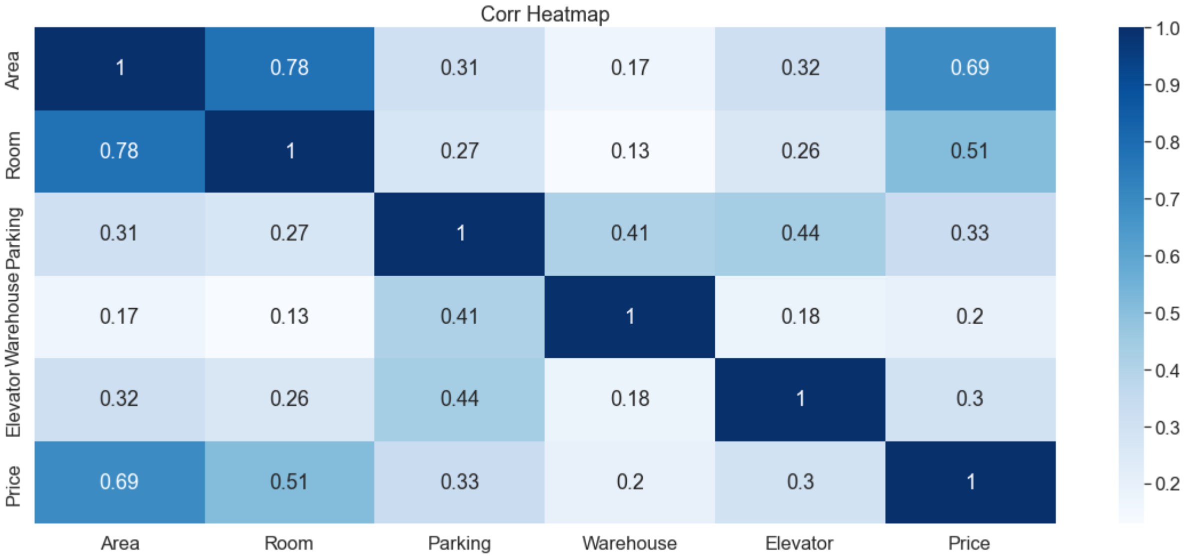





```
Here is the skewness after droping outliers Area         0.672756
Room         0.163801
Parking     -1.798618
Warehouse   -2.901748
Elevator    -1.393130
Price        1.285909
dtype: float64
```

In [44]:

```python
# heatmap of correlation between features
plt.figure(figsize=(20, 8))
ax = sns.heatmap(housePri.corr(), annot=True, cmap='Blues')
ax.set_title('Corr Heatmap', fontdict={'fontsize': 18})
plt.show()
```

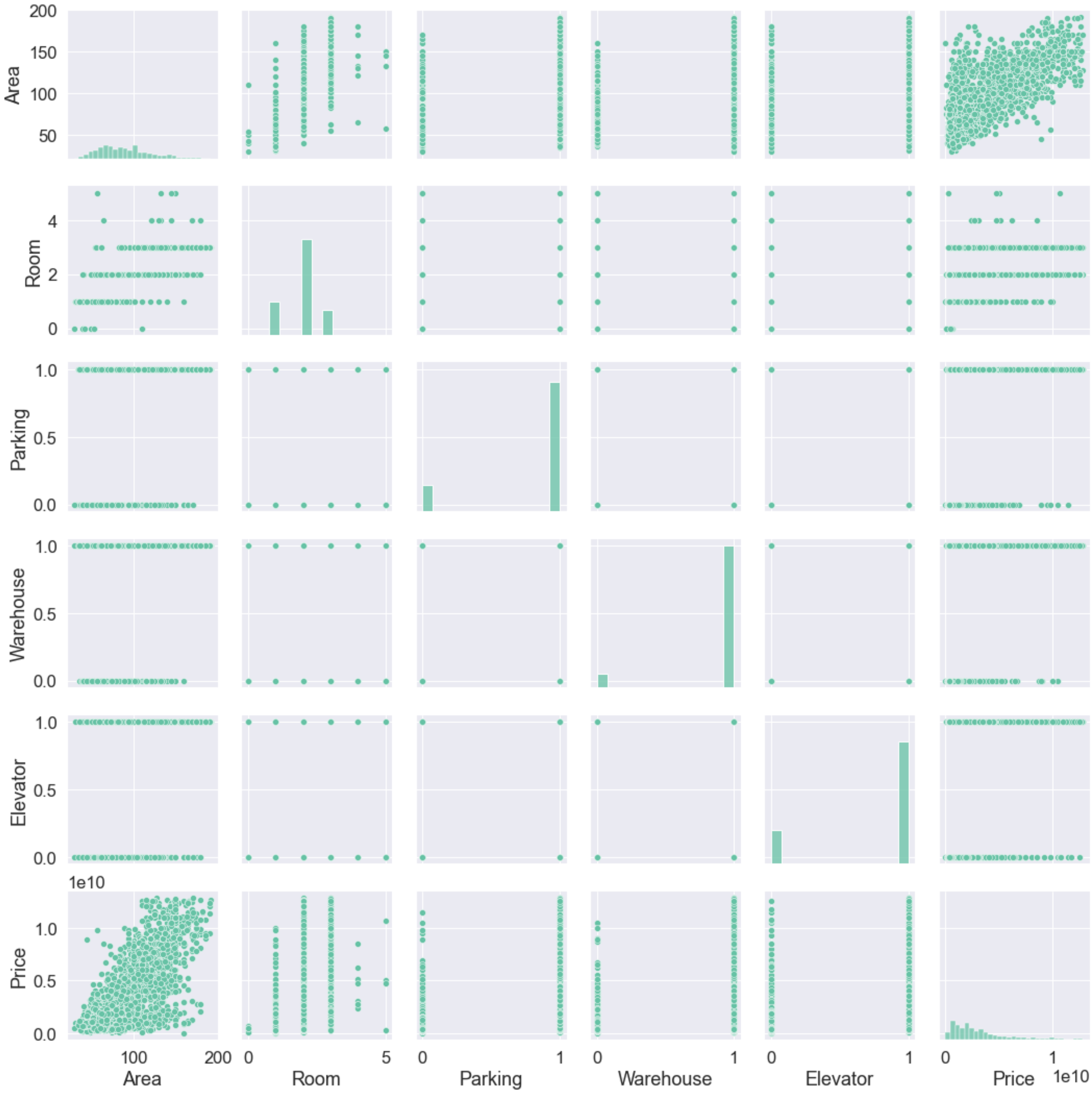


In [45]:

```python
#let me also check cross correlation of the data using pairplot of the whole datase
sns.pairplot(housePri)
```

Out[45]:

```
<seaborn.axisgrid.PairGrid at 0x22fc8d62f40>
```



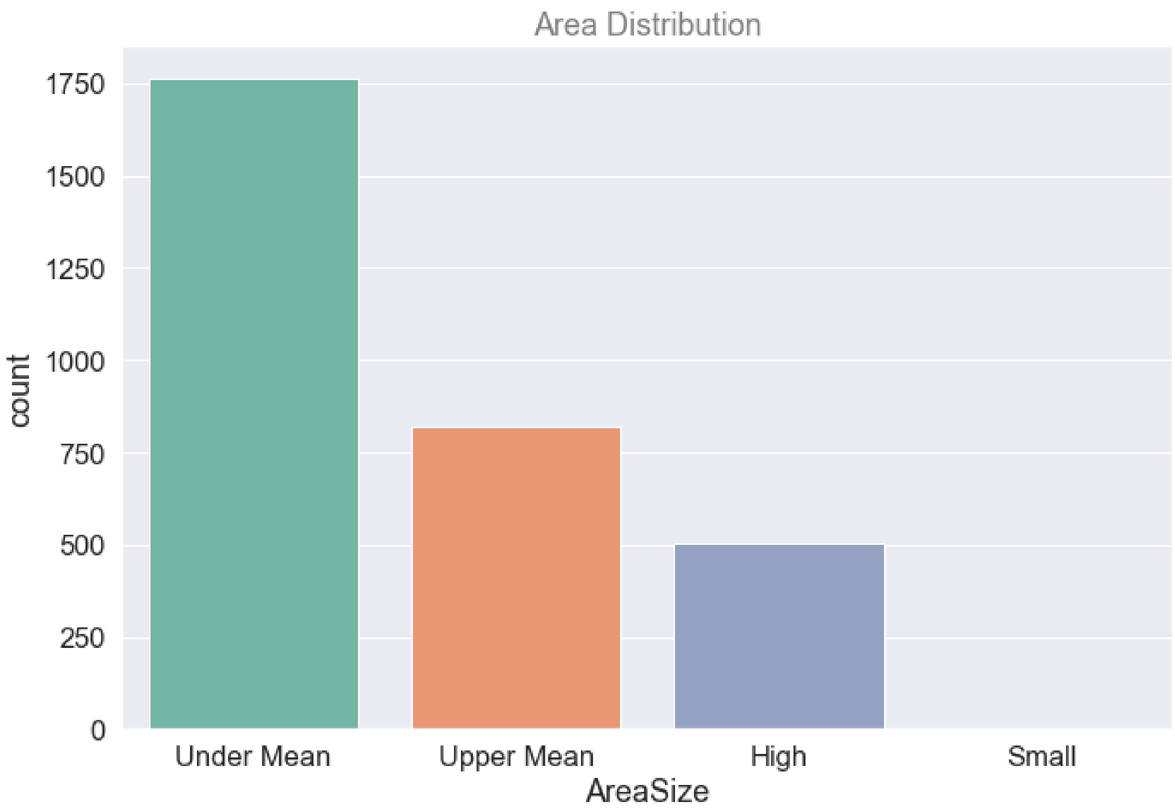
The above is the result after removing outliers and nan values.

FEATURE ENGINEERING

In [46]:
```
AreaNewFeat = []

for i in housePri['Area']:
    if i <= 30:
        AreaNewFeat.append("Small")

    elif (i > 30 and i<=90):
        AreaNewFeat.append("Under Mean")

    elif (i>90 and i <= 120):
        AreaNewFeat.append("Upper Mean")

    elif i > 120:
        AreaNewFeat.append("High")
    else:
            AreaNewFeat.append(np.nan)

housePri["AreaSize"] = AreaNewFeat
```

In [47]:
```
plt.figure(figsize=(10,7))
sns.countplot(x="AreaSize" , data= housePri)
```

```
plt.title("Area Distribution" , color='gray')
plt.tight_layout()
```

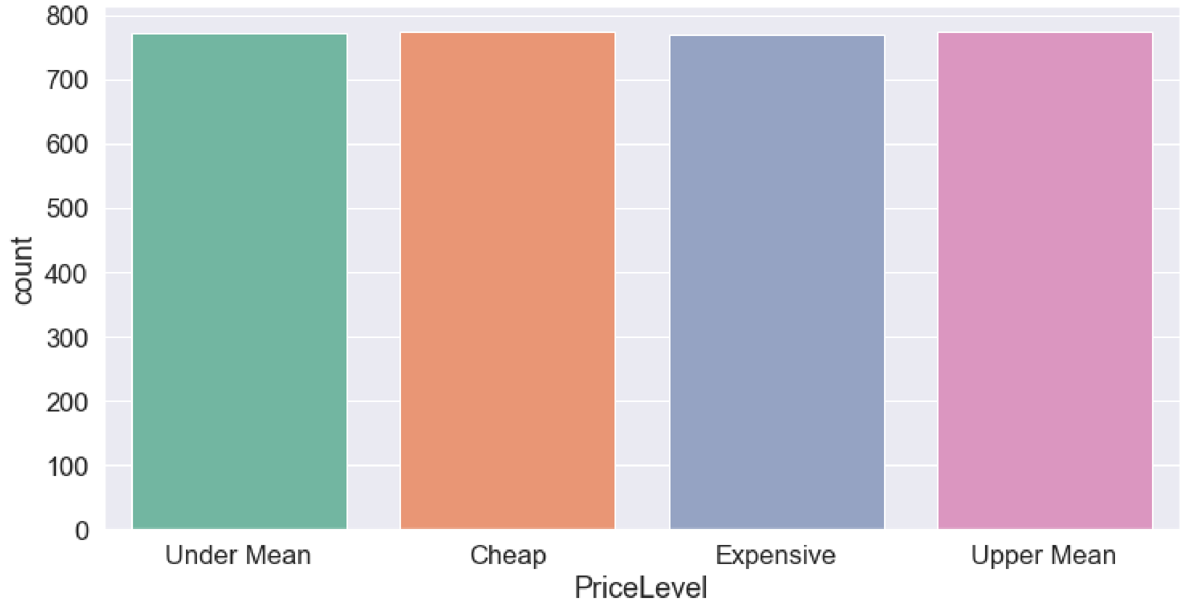


Insight > As we can see about half of houses have between 30-90 meters(m2) > Houses with 90-120 meters have the same contribution with houses which have more than 120 meters > we can realize that right-skewed has happened.(outliers most are on the right part) > very low houses are with less than 30 meters size.

In [48]:
```
PriceNewFeat = []

H25 = housePri['Price'].describe()[4]
H50 = housePri['Price'].describe()[5]
H75 = housePri['Price'].describe()[6]

for i in housePri['Price']:

    if    i <= H25:
        PriceNewFeat.append("Cheap")

    elif (i > H25 and i<= H50):
        PriceNewFeat.append("Under Mean")

    elif (i > H50 and i <= H75):
       PriceNewFeat.append("Upper Mean")

    elif  i > H75:
        PriceNewFeat.append("Expensive")

    else:
        PriceNewFeat.append(np.nan)

housePri["PriceLevel"] = PriceNewFeat
```

In [49]:
```
plt.figure(figsize=(12,6))
sns.countplot(x='PriceLevel' , data = housePri )
```

Out[49]:
```
<AxesSubplot:xlabel='PriceLevel', ylabel='count'>
```



The price level across the region is been regularized based on the price mean.

RESEACH QUESTIONS

4.1 WHAT IS BEING ANALYSED?

1. Aim and Objectives of this reseach analysis is to develop a machine learning model to predict the price of houses

2. The project focussed on supervised learning techniques using regression methods

4.4 How is it being analysed?

1. Regression Analysis:

```
    The target variable is House Price(descrete numerical data),
which is dependant variable and other columns area, room, parking,
warehouse, elevator and location are independent variable. We
perform regression analysis to identify the relation between these
dependent and independent variables and build our model. This
model will then predict the price information for the given
independent variables(features).
```

4.4.1 Suitable Algorithms - Regrerssion Analysis

1. Ridge 2. Random Forest Regressor 3. XGBRegressor 4. Lasso Regressor 5. Elastic Network 6. KNeighbour Regressor 7. Decision Tree Regressor

DATA PREPARATION FOR REGRESSION

In [50]:

```
housePri["Area"] =housePri['Area'].astype('int')
pd.options.display.float_format = '{:.0f}'.format
```

```python
#housePri["Price"] =housePri['Price'].astype('int')
housePri.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3089 entries, 0 to 3478
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Area        3089 non-null   int32  
 1   Room        3089 non-null   int64  
 2   Parking     3089 non-null   int32  
 3   Warehouse   3089 non-null   int32  
 4   Elevator    3089 non-null   int32  
 5   Address     3089 non-null   object 
 6   Price       3089 non-null   float64
 7   AreaSize    3089 non-null   object 
 8   PriceLevel  3089 non-null   object 
dtypes: float64(1), int32(4), int64(1), object(3)
memory usage: 257.6+ KB
```

In [51]:
```python
housePri.head(15)
```

Out[51]:

	Area	Room	Parking	Warehouse	Elevator	Address	Price	AreaSize	PriceLevel
0	63	1	1	1	1	Shahran	1850000000	Under Mean	Under Mean
1	60	1	1	1	1	Shahran	1850000000	Under Mean	Under Mean
2	79	2	1	1	1	Pardis	550000000	Under Mean	Cheap
3	95	2	1	1	1	Shahrake Qods	902500000	Upper Mean	Cheap
4	123	2	1	1	1	Shahrake Gharb	7000000000	High	Expensive
5	70	2	1	1	0	North Program Organization	2050000000	Under Mean	Under Mean
6	87	2	1	1	1	Pardis	600000000	Under Mean	Cheap
7	59	1	1	1	1	Shahran	2150000000	Under Mean	Under Mean
8	54	2	1	1	0	Andisheh	493000000	Under Mean	Cheap
9	71	1	1	1	1	West Ferdows Boulevard	2370000000	Under Mean	Under Mean
10	68	2	1	1	1	West Ferdows Boulevard	2450000000	Under Mean	Under Mean
11	64	1	1	1	1	Narmak	2100000000	Under Mean	Under Mean
12	54	1	0	1	1	Narmak	1690000000	Under Mean	Under Mean
13	136	3	1	1	1	Saadat Abad	11000000000	High	Expensive
14	95	2	1	1	1	Zafar	5000000000	Upper Mean	Expensive

GET DUMMY FOR THE ADDRESS

In [52]:

```
addr_dum = pd.get_dummies(housePri[['Address','AreaSize','PriceLevel']])
housePrice = housePri.merge(addr_dum, left_index = True, right_index = True)
housePrice.drop(columns = {'Address','AreaSize','PriceLevel'}, inplace = True)
housePrice.head(10)
```

Out[52]:

	Area	Room	Parking	Warehouse	Elevator	Price	Address_Abazar	Address_Abbasabad
0	63	1	1	1	1	1850000000	0	0
1	60	1	1	1	1	1850000000	0	0
2	79	2	1	1	1	550000000	0	0
3	95	2	1	1	1	902500000	0	0
4	123	2	1	1	1	7000000000	0	0
5	70	2	1	1	0	2050000000	0	0
6	87	2	1	1	1	600000000	0	0
7	59	1	1	1	1	2150000000	0	0
8	54	2	1	1	0	493000000	0	0
9	71	1	1	1	1	2370000000	0	0

10 rows × 201 columns

In other to convert Address, AreaSize and Pricelevel to integer as required by machine learnign algorithm i get the dummy values for each feature. as show above. I merged the dummy value to the dataset then I drop Address, AreaSize and Pricelevel column

SPLIT DATA TO TARGET AND INPUT VARIABLES

In [53]:

```
X=housePrice.drop(['Price'], axis=1)
Y=housePrice['Price']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X,Y, test_size=0.2, random_state

print(f"shape of x train: {X_train.shape}")
print(f"shape of y train: {y_train.shape}")
print(f"shape of x test: {X_test.shape}")
print(f"shape of y train: {y_test.shape}")
```

```
shape of x train: (2471, 200)
shape of y train: (2471,)
shape of x test: (618, 200)
shape of y train: (618,)
```

DATA SCALING

In [54]:

```
#let scale the x_train and x_test
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [55]:

```
Model_Name  = []
Train_score = []
Test_score  = []
MSE_s    = []
RMSE_s   = []
MAE_s=[]
Accuracy=[]
```

In [56]:
```
def find_param (model, parameters):

    grid = GridSearchCV(model,
                        param_grid = parameters,
                        refit = True,
                        cv = KFold(shuffle = True, random_state = 1),
                        n_jobs = -1)
    grid_fit = grid.fit(X_train, y_train)
    y_train_pred = grid_fit.predict(X_train)
    y_pred = grid_fit.predict(X_test)


    train_score =grid_fit.score(X_train, y_train)
    test_score = grid_fit.score(X_test, y_test)
    RMSE = np.sqrt(mean_squared_error(y_test, y_pred))
    MSE = mean_squared_error(y_test, y_pred)
    MAE = mean_absolute_error(y_test, y_pred)
    model_name = str(model).split('(')[0]

    Model_Name.append(model_name)
    Train_score.append(train_score)
    Test_score.append(test_score)
    Accuracy.append(round(test_score*100,1))
    MSE_s.append(MSE)
    RMSE_s.append(RMSE)
    MAE_s.append(MAE)



    print(f"The best parameters for {model_name} model is: {grid_fit.best_params_}
    print("--" * 10)
    print(f"(R2 score) in the training set is {train_score:0.2%} for {model_name} 
    print(f"(R2 score) in the testing set is {test_score:0.2%} for {model_name} mo
    print(f"RMSE is {RMSE:,} for {model_name} model.")
    print(f"MSE is {MSE:,} for {model_name} model.")
    #print(y_pred)
    print("--" * 10)


    return train_score, test_score, RMSE,MSE, y_pred
```

The above function will be apply on all algorithm to find the best parameters for better prediction

RIDGE REGRESSOR MODEL

In [57]:
```
ridge = Ridge(random_state = 1) # Linear least squares with l2 regularization.
ridge_para = {'alpha': [0.001, 0.01, 0.1, 1, 10]}

rg_train_score, rg_test_score, rg_RMSE,rg_MSE, y_preRig = find_param(ridge, ridge_
```

```
The best parameters for Ridge model is: {'alpha': 10}
--------------------
(R2 score) in the training set is 91.32% for Ridge model.
(R2 score) in the testing set is 90.96% for Ridge model.
RMSE is 830,286,604.5457253 for Ridge model.
MSE is 6.893758456880698e+17 for Ridge model.
--------------------
```

LASSO REGRESSOR

In [58]:
```
lassoReg = Lasso(random_state = 1) # Linear Model trained with L1 prior as regular
las_para = {'alpha': [0.001, 0.01, 0.1, 1, 10]}

lasTrain_score, lasTest_score, lasRMSE,lasMSE, las_y_predL = find_param(lassoReg,la
```

```
The best parameters for Lasso model is: {'alpha': 10}
--------------------
(R2 score) in the training set is 91.32% for Lasso model.
(R2 score) in the testing set is 90.97% for Lasso model.
RMSE is 829,480,774.3388903 for Lasso model.
MSE is 6.880383549978451e+17 for Lasso model.
--------------------
```

RANDOM FOREST REGRESSOR MODEL

In [59]:
```
forest= RandomForestRegressor(random_state = 1, n_jobs = -1)
param_forest = {'min_samples_split': [2,4],
            'max_depth': [None,4,8],
            'n_estimators' : [100,200,300],'max_features':[0.8,0.9]}

rfr_train_score, rfr_test_score, rfr_RMSE,rfr_MSE, y_pre = find_param(forest, para
```

```
The best parameters for RandomForestRegressor model is: {'max_depth': None, 'max_f
eatures': 0.8, 'min_samples_split': 4, 'n_estimators': 100}
--------------------
(R2 score) in the training set is 97.92% for RandomForestRegressor model.
(R2 score) in the testing set is 93.58% for RandomForestRegressor model.
RMSE is 699,743,136.9846356 for RandomForestRegressor model.
MSE is 4.896404577570985e+17 for RandomForestRegressor model.
--------------------
```

XG BOOST REGRESSOR

In [60]:
```
xgboost = XGBRegressor(n_jobs = -1)
param_xgboost = {'n_estimators': [100,300],
             'learning_rate': [0.1,0.05],
             'subsample': [0.75],
             'colsample_bytree': [1],
             'max_depth': [3,4,5],
             'gamma': [0]}

xgb_train_score, xgb_test_score, xgb_RMSE,xgb_MSE, y_preX = find_param(xgboost, pa
```

```
The best parameters for XGBRegressor model is: {'colsample_bytree': 1, 'gamma': 0,
'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 300, 'subsample': 0.75}
--------------------
(R2 score) in the training set is 95.62% for XGBRegressor model.
(R2 score) in the testing set is 93.39% for XGBRegressor model.
RMSE is 710,013,902.3680446 for XGBRegressor model.
MSE is 5.0411974155589926e+17 for XGBRegressor model.
--------------------
```

ElasticNet model

In [61]:
```
elas = ElasticNet(random_state = 1) # Linear regression with combined L1 and L2 pr
ePram = {'alpha': [0.001, 0.01, 0.1, 1, 10],
            'l1_ratio': [0.3, 0.4, 0.5, 0.6, 0.7, 0.8,0.9]}

eTtrain_score, eTest_score, eRMSE,eMSE, y_predE = find_param(elas, ePram)
```

```
The best parameters for ElasticNet model is: {'alpha': 0.1, 'l1_ratio': 0.8}
--------------------
(R2 score) in the training set is 91.30% for ElasticNet model.
(R2 score) in the testing set is 90.88% for ElasticNet model.
RMSE is 833,956,532.4863738 for ElasticNet model.
MSE is 6.954834980766962e+17 for ElasticNet model.
--------------------
```

KN NEIGHBOUR REGRESSOR

In [62]:
```
Kregress = KNeighborsRegressor(n_jobs = -1)
kPram = {'n_neighbors': [5, 10, 15, 20],
         'weights': ['uniform', 'distance']}

knTrain_score, knTest_score, knRMSE,knMSE,y_predKn = find_param(Kregress, kPram)
```

```
The best parameters for KNeighborsRegressor model is: {'n_neighbors': 20, 'weight
s': 'distance'}
--------------------
(R2 score) in the training set is 99.43% for KNeighborsRegressor model.
(R2 score) in the testing set is 89.49% for KNeighborsRegressor model.
RMSE is 895,013,038.9223047 for KNeighborsRegressor model.
MSE is 8.01048339840939e+17 for KNeighborsRegressor model.
--------------------
```

In [63]:
```
## Decision Tree Regressor
```

In [64]:
```
DecTr = DecisionTreeRegressor(random_state = 1)
dec_param = {'min_samples_split': [2,3,4, 5],
            'min_samples_leaf': [1, 2, 3]}

dtr_train_score, dtr_test_score, dtr_RMSE,dtr_MSE, y_predDec = find_param(DecTr, d
```

```
The best parameters for DecisionTreeRegressor model is: {'min_samples_leaf': 3, 'm
in_samples_split': 2}
--------------------
(R2 score) in the training set is 95.25% for DecisionTreeRegressor model.
(R2 score) in the testing set is 90.35% for DecisionTreeRegressor model.
RMSE is 857,655,986.6890824 for DecisionTreeRegressor model.
MSE is 7.355737915036236e+17 for DecisionTreeRegressor model.
--------------------
```

Neural Network

In [65]:
```
nn_model = MLPRegressor()
nn_param = \
    {
        "hidden_layer_sizes": [(7,)*3, (19,), (100,), (154,)],
        "activation": ["identity", "logistic", "tanh", "relu"],
        "solver": ["lbfgs"],
        "alpha": [1, 10, 100],
    }
nn_train_score, nn_test_score, nn_RMSE,dtr_MSE, y_predNn = find_param(nn_model, nn_
```

```
The best parameters for MLPRegressor model is: {'activation': 'relu', 'alpha': 10,
'hidden_layer_sizes': (19,), 'solver': 'lbfgs'}
--------------------
(R2 score) in the training set is 96.38% for MLPRegressor model.
(R2 score) in the testing set is 92.45% for MLPRegressor model.
RMSE is 758,859,262.6933253 for MLPRegressor model.
MSE is 5.758673805754573e+17 for MLPRegressor model.
--------------------
```

In [66]:

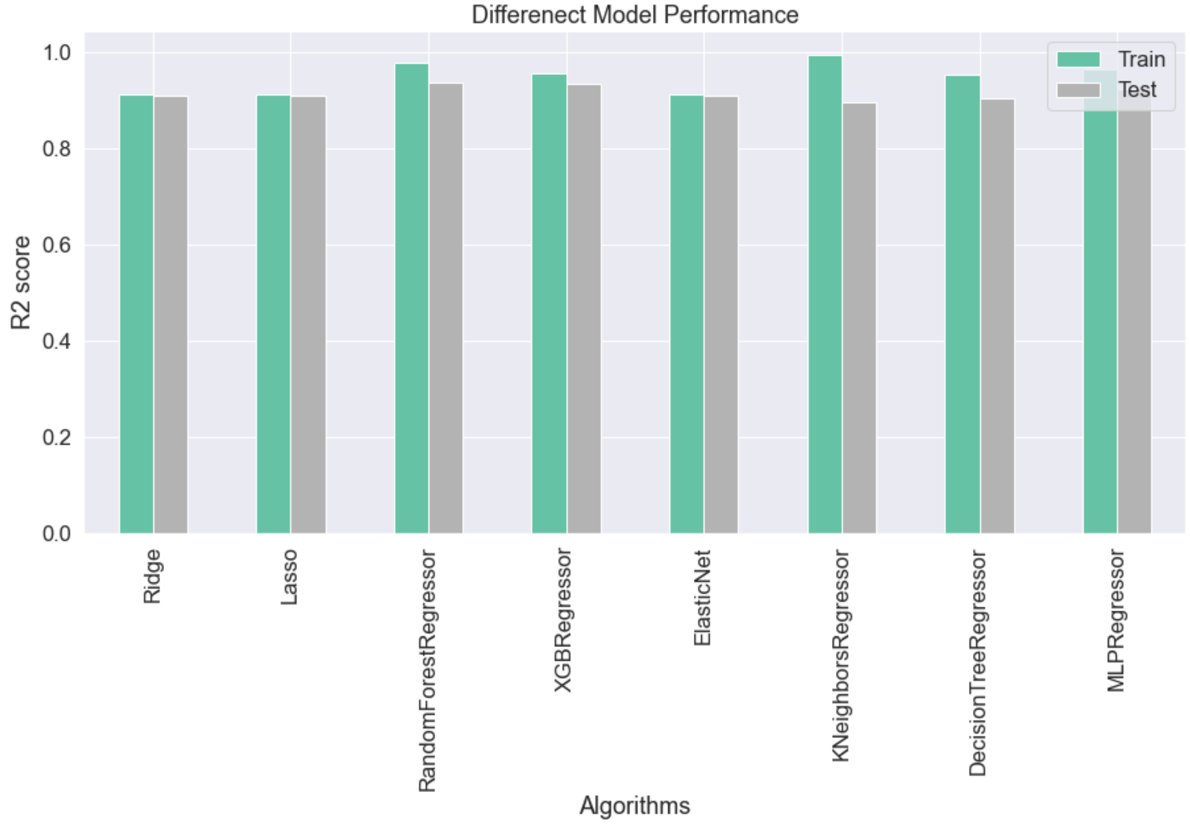
```python
pd.reset_option("all")
R_data = pd.DataFrame({'Algorithms':Model_Name,
            'Train':Train_score ,
            'Test':Test_score ,
            'Accuracy':Accuracy,
            'MSE' :MSE_s,
            'RMSE':RMSE_s,
            'MAE':MAE_s})
R_data.set_index('Algorithms', inplace=True)
R_data.sort_values(by=['MAE'])
```

Out[66]:

Algorithms	Train	Test	Accuracy	MSE	RMSE	MAE
RandomForestRegressor	0.979239	0.935768	93.6	4.896405e+17	6.997431e+08	3.924720e+08
XGBRegressor	0.956164	0.933868	93.4	5.041197e+17	7.100139e+08	4.550615e+08
MLPRegressor	0.963829	0.924456	92.4	5.758674e+17	7.588593e+08	4.583499e+08
DecisionTreeRegressor	0.952451	0.903505	90.4	7.355738e+17	8.576560e+08	4.837702e+08
ElasticNet	0.912969	0.908764	90.9	6.954835e+17	8.339565e+08	5.090714e+08
Ridge	0.913214	0.909566	91.0	6.893758e+17	8.302866e+08	5.112731e+08
Lasso	0.913229	0.909741	91.0	6.880384e+17	8.294808e+08	5.123537e+08
KNeighborsRegressor	0.994283	0.894916	89.5	8.010483e+17	8.950130e+08	5.158643e+08

In [68]:

```python
R_data.plot(y = ['Train' , 'Test'] , kind="bar" , figsize=(15,7) ,title="Differene
plt.ylabel('R2 score')
plt.show()
```



In [69]:
```
R_data.plot(y = ['MAE'] , kind="bar" , figsize=(15,7) ,title="MAE for different mo
plt.ylabel("MAE(smaller the better)")
plt.show()
```